Proactive Energy Management for High-Performance Buildings: Exploiting and Motivating New Sensor Technologies

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***Abstract*—We discuss how sensor technologies have enabled the development of proactive energy management (EM) systems. At the same time, we discuss how these emerging EM systems motivate the development of new sensor technologies. Proactive EM systems integrate advances in weather forecasting, sensors, predictive models, and real-time optimization algorithms to anticipate uncertain factors that affect energy performance and costs and make real-time set-point corrections (AHU delivery conditions, ventilation rates, thermostats) to modulate them. On-going deployment studies have found that up to 30% HVAC energy savings are achievable using this type of technologies. We describe extensions of these systems to exploit emerging sensor technologies including occupancy, ventilation, and air quality sensors.**

I. Motivation

Proactive energy management (EM) systems can play a significant role in achieving energy efficiency targets and can also make buildings more active participants in smart grid environments [1]. These EM systems exploit sensor data and predictive building models to allow for a more proactive modulation of building energy usage as external weather, occupancy, and market signals change while ensuring occupant thermal comfort and air quality.

A key novelty of this approach is that it enables energy demand forecasting which can be used to coordinate the operation of heating ventilation and air conditioning (HVAC) systems and storage devices (e.g., ice storage) and thus enable a more active building participation in several markets such as day-ahead and real-time pricing markets, demand and reserves markets, and ancillary services markets that central grid operators can exploit to modulate grid contingencies and supply fluctuations. This can significantly enhance the flexibility of the power grid, which is critical to adopt renewable generation. *In order to fulfill this vision, however, it is necessary to develop scalable energy management solutions that are flexible, inexpensive and easy to deploy, thus allowing for wide-spread deployment.*

Existing building management systems (BMS) serve mostly as interfaces for building operators to monitor sensor data and modify operational (set-point) conditions of air-handling units, thermostats, chillers, ice storage, and other devices as occupancy, weather, and price conditions change throughout the day in order to minimize energy costs and satisfy occupant thermal comfort. These systems are equipped with basic controllers that track the set-points dictated by the human operator or by the EM system which normally consists of a set of optimization functions or rules that are tuned to minimize energy (e.g., precooling and economizer control) [6].

A limitation of existing EM systems or functions is that they are inherently reactive and cannot accurately capture multivariable interactions [4]. In other words, they lack mechanisms to systematically predict and anticipate the integrated effect of weather, occupancy, building design, and market prices on the building dynamic response, energy demands and costs, and comfort conditions. This lack of predictive knowledge limits the exploitation of the building dynamic momentum to reduce and energy and to ensure a strict satisfaction of comfort conditions. In addition, it limits the participation of the building on electricity markets. For instance, buildings are normally price-takers and participate sporadically on demand response events during extreme power grid contingencies. This situation can expose buildings to the high volatility of real-time prices and discourages investment in sensors, automation, and storage technologies. The lack of predictive knowledge in existing EM systems, in addition, underestimates the value of the building active and passive storage assets by utility companies, independent system operators (ISOs), and regional transmission operators.

Recently, proactive energy management systems have emerged as a promising alternative for building automation [12], [1], [13], [9], [8]. These systems use of predictive models to automatically and dynamically optimize the operating conditions of the HVAC system (e.g., air supply and chiller set-points) and of the building (e.g., thermostat set-points) to minimize energy consumption and maintain comfort conditions as internal occupancy and external ambient conditions change throughout the day. We highlight that these systems can indeed reduce energy consumption and not only energy costs which has been the main driver behind peak-shifting strategies [2], [3]. Existing commercial vendors of this type of technology include BuildingIQ [15] and Clean Urban Energy.

The use of predictive models enables the coordination of building thermal momentum with dynamic trends of weather, occupancy, and prices. The use of predictive models also enables the system to quantify and anticipate the effect of the building internal and external conditions on energy demands and economic performance. Notably, predictive models can be constructed based on data-based (also called statistical or machine learning) techniques that exclusively use available *sensor*

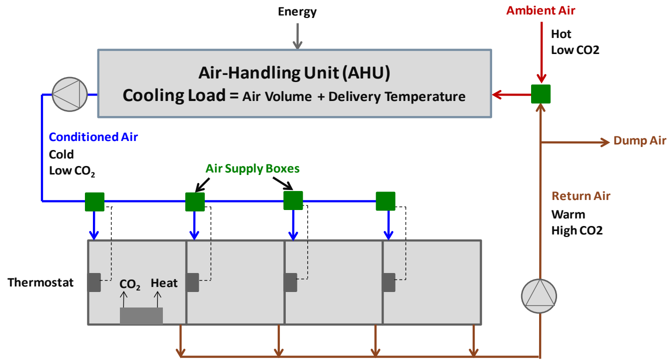

Fig. 1. Schematic representation of interface between air-handling unit and building (cooling mode).

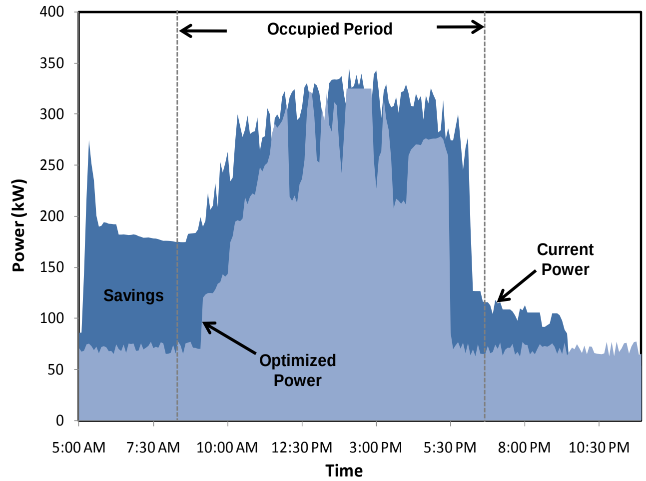

Fig. 2. Typical energy savings profile of proactive EM system.

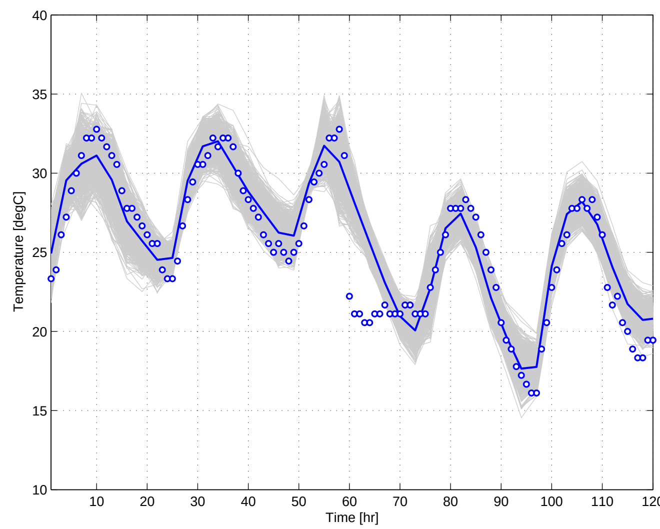

Fig. 3. Five day ahead ambient temperature forecast and uncertainty information obtained with numerical weather prediction WRF. Dots are real measurements.

data and minimal building topology information [12], [15], [6]. This approach enables a high degree of modularity, low technological costs, and fast deployment times. The impact of this type of technology, however, strongly depends on the availability of low-cost, flexible, and robust sensor networks that enable a sufficient observability and controllability of the building environment.

In this short note we highlight the principles behind proactive energy management and describe how emerging sensor technologies (occupancy, air quality) can be exploited by these systems to maximize energy savings while satisfying comfort and air quality requirements [12], [7], [13]. In addition, we discuss how the deployment of these more advanced real-time optimization strategies has started to indicate needs in sensor technologies. *Consequently, we argue that a more integrated approach to EM systems and sensor development is necessary in order to minimize deployment costs and maximize energy savings and deployment.*

II. Proactive Energy Management

A typical electric HVAC system is illustrated in Fig. 1 and 2. Ambient air at prevailing temperature, humidity and pollutant conditions (CO_2,CO, VOCs, particles) is conditioned in an air-handling unit (AHU). (More complex configurations than that in Fig. 2 use chillers and ice storage to provide the cooling load to the AHU.) Humidity is modulated using a humidifier/dehumidifier that cools the mixture down to remove latent energy in the air. The mixture is further cooled to remove sensible heat and achieve the cooling load required by the building. The cooling load can be achieved by finding appropriate conditions for supply temperature and air volume. The conditioned air is distributed to the building zones using air dampers. The dampers are in closed loop with thermostats that sense the zone temperature as internal conditions change. Internal changes include heat gains due to occupants, equipment, and thermal loads resulting from external solar radiation and wind convection. The zone air is removed continuously from the zones and recycled to the AHU. This is mixed with ambient air to close the cycle. Depending on the ambient conditions, optimal combinations of ambient and recycle air can be exploited to save energy in the AHU. The external ventilation rate, however, is currently constrained by minimum rates set by ASHRAE standard 62 based on the estimated number of occupants.

Proactive energy management systems use weather forecasts and predictive dynamic models of the building zones to anticipate and exploit weather and internal condition trends to minimize the cooling load in the AHU while satisfying thermal comfort of the occupants (e.g., using PMV and PPD metrics [10]). A key principle is that the building has sufficient dynamic momentum or thermal mass to withhold the conditioned air internally over extended periods of time without affecting comfort conditions. This basic synchronization principle is key in saving energy and in modulating demands throughout the day [6]. In Fig. 2 we present the base and optimized power profiles for an AHU operating at Argonne National

Laboratory using BuildingIQ technology [15]. We note that 20-30% electricity savings can be realized during off-peak and peak times even under strict comfort conditions. As explained in [15], the peak demand can be further decreased by relaxing comfort conditions at critical times.

Proactive systems perform comfort modulation by exploiting the building momentum and by direct feedback from occupants to minimize occupancy dissatisfaction. This is a notable difference with existing EM practice that fixes the building temperature conditions that are believed to be comfortable for the entire occupant population. This can significantly increase energy demands since perceived comfort varies due to many other other factors including metabolism, age, clothing, and so on. In addition, proactive systems can exploit periods of no occupancy to relax comfort conditions and minimize HVAC energy as well as to store ambient air in the building and thus minimize unnecessary air conditioning [15].

Several technological advances make possible the development and low-cost deployment of proactive energy management systems. The first is the availability of sensor information. Sensor data is necessary to observe and quantify the performance of the building. In addition, low-cost sensors are necessary since a large share of sensors is usually needed to capture the distributed nature of buildings. The second enabler is the availability of data-based or statistical modeling techniques [11] that enable the creation of low-cost and adaptive building models using available sensor data and minimal building topological information.

The third important advances are numerical weather prediction (NWP) models. These systems are currently capable of providing accurate forecasts of key variables that drive building energy demands such as ambient temperature, humidity, wind speed and direction, and solar radiation. In Fig. 3 we present a five-day-ahead forecast and uncertainty information obtained with the NWP model WRF, developed by several federal agencies, including the National Oceanic and Atmospheric Administration. This system is currently in operational mode at the Mathematics and Computer Science Division at Argonne National Laboratory and has been used extensively to estimate economic benefits of weather forecasting in power grid and building operations [1], [4], [14]. Note the remarkable predictive capabilities of the NWP model for the ambient temperature, the most critical variable driving HVAC electricity demand. As expected, merging weather forecasts with building sensors and predictive models results in a powerful paradigm to anticipate and modulate building demands. In addition, it can provide valuable demand forecast information to power grid operators. This is a key capability of EM systems in future smart grid environments.

III. Exploiting Emerging Sensor Technologies

One of the key enablers in satisfying occupant comfort and reducing energy intensity using automated EM systems is the availability of information of the building physical (air quality, humidity, temperature) and non-physical conditions (occupant number and location, heat loads).

Fig. 4. Occupant movement in commercial-sized building.

In the case of occupancy, occupants are currently counted according to their associated with their fixed physical space (e.g., office) and average behavior. Occupants, however, move constantly throughout the building, implicitly affecting the distribution of energy and efficiency of the HVAC system. In Figure 4, we present a snapshot of occupant locations at a building in Argonne. As can be seen, significant portions of the building are unoccupied and thus present an opportunity for energy savings. The key obstacle, however, is the ability of the system to quantify the number of occupants to optimize ventilation rates at the central HVAC level and at disaggregated zone levels. In the absence of an accurate occupancy count, extremely high (and difficult to measure) ventilation rates are enforced in order to maintain operation compliant with ASHRAE 62 standard which requires a minimum ventilation rate per occupant to maintain pollutants at safe levels. The use of conservative ventilation rates has been identified as one of the most important sources of energy inefficiency in commercial buildings since it limits recirculation and requires constant reconditioning of external ambient air [7], [5]. For instance, the number air changes per hour in typical buildings can be on the order of 3-6. Considering the massive amounts of air contained in a commercial-sized building, this represents a significant source of inefficiency. Surrogate CO_2 models coupled to CO_2 sensors can be exploited to infer occupancy count in different parts of the building. A central CO_2 sensor in the return duct of the HVAC system can be used to estimate total occupancy count and estimate the minimum ventilation rates. Installing CO_2 sensors at individual zones can also be used (in principle) to optimize local ventilation rates. Another strategy to estimate occupancy count consists in using imaged-based sensor technologies. This strategy is more informative since it not only provides occupancy count but also CO_2 and thermal loads. This reduces the uncertainty associated to infiltration/exfiltration rates. A key obstacle in exploiting occupancy information in disaggregated ventilation control, however, is that ventilation rates are manipulated by VAV boxes that try to control the zone temperature. A strategy to bypass this limitation is to change the delivery temperature

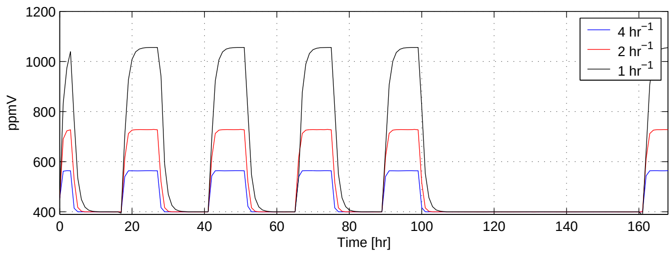

Fig. 5. Simulated CO_2 dynamics under variable ventilation rates.

of the supply air to implicitly control the VAV ventilation rate [12]. An important limitation of inferring occupancy through CO_2 sensors, however, is the limited availability of infiltration/exfiltration rate information which can significantly bias the occupancy estimates.

The use of predictive models of air quality conditions in proactive EM systems has the potential of saving significant amount of energy. This is based on the observation that pollutant dynamics are significantly slow so that ventilation rates can be minimized during occupied times without affecting the air quality inside the building during occupied conditions so that building purge can be performed at night during unoccupied conditions. Simulation studies have shown that over 50% HVAC energy savings are possible. A key obstacle in deploying this type of strategies, however, is that the existing ASHRAE standard 62 takes limited building dynamics into account, which vary significantly with the ventilation rates themselves. In Fig. 5, we present the dynamics of CO_2 under two different ventilation policies.

Simulation studies have also shown that per-occupant ventilation rates can optimized dynamically using proactive systems without reaching perceptible pollutant concentrations [13]. In order to achieve this vision, EM systems it is critical to develop low-cost indoor air quality (IAQ) sensors that can be used to control air quality conditions directly instead of indirectly through ventilation rates. We highlight that the lack of IAQ information coupled to the lack of EM systems capable of exploiting it efficiently *is perhaps the most significant obstacle in achieving large-scale energy savings in existing and new buildings*.

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